Cross Training Policies in a Maintenance Field Service Organization

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Abstract. As the trend towards more after sales service progresses through the industrial equipment industry, equipment manufacturers are offering comprehensive service contracts in which they take full responsibility for the functioning of their customers' machines. These contracts increase the importance of capacity decisions in maintenance field operations. We evaluate the possibility to deploy technicians dedicated to preventive maintenance instead of fully cross trained technicians based on a real case in the compressed air industry. Our contribution consists of identifying the factors that influence the optimal cross training policy while taking into account the effect of the capacity decisions on the maintenance demand.

Keywords: Cross training, Field service, Service contracts, Simulation

1 Introduction

Original equipment manufacturers (OEMs) such as GE, Rolls-Royce and Siemens have recognizing the importance of after sales service [1]. These manufacturers pursue a product service strategy in which they actively promote services to enhance the value proposition of their product offering.

The professionalization of the aftermarket service industry has led to a surge in the use of multi-period service contracts. In some of these contracts service providers take full responsibility for the functioning of the equipment and sometimes they even give up-time guarantees (performance based contracting). With such contracts in place, demand for service can be influenced by the OEM by setting proper maintenance policies and corresponding capacity levels. By taking responsibility for the entire maintenance of the machine, the OEM will be able to perform more preventive maintenance which translates itself in less repairs. In this way the OEM can steer its service organization towards more planned and less emergency activities. Therefore, comprehensive contracts offer the possibility to lower the uncertainty in the service demand which creates opportunities to optimize the service operations [2]. Typically maintenance organizations have to deal with two types of tasks. On the one hand they will need to fix machines that have failed (repairs or corrective maintenance). On the other hand they will try to avoid failures by performing preventive maintenance. Contrary to preventive maintenance, repairs cannot be planned and have to be dealt with in an "as soon as possible" manner. To highlight this difference we will indicate repairs with the term “emergencies” while preventive maintenance jobs are referred to as “non emergencies”. Given that technicians require different skills for different machine types and different types of service, i.e. emergency or non emergency service, it is a daunting task to ensure that there is always a properly trained technician nearby to provide service to the customer when required. The easiest way to deal with this problem is to fully cross train all technician. However, this option may be prohibitive expensive, therefore many service organizations will have technicians that are trained for specific tasks or technologies. In this paper we report on our research concerning the cross training trade-off in a field service organization. To the best of our knowledge, we are the first to study the cross training decision in a field service context with comprehensive maintenance contracts. We define a cross training policy as the decision about how many technicians should be trained for a specific skill set. In this paper we limit ourselves to two skill sets depending on the type of service, viz. emergency and non emergency service.

In section two we will present the related literature. In section three the assumptions of the simulation model will be explained. Section four discusses the results and we conclude in section five.

2 Literature review

There are two broad fields of literature related to our research. Firstly, our work adds to the literature on capacity planning in service operations with a focus on cross training strategies.

Stochastic traveling times and the sequence dependency of these travel times render capacity management in a field service setting especially challenging. Given this complexity it is hardly surprising that most studies apply a simulation model to study cross training decisions ([3], [4], [5], [6]). Analytical work in the area of field service capacity planning applies queuing theory to determine steady-state performance measures, e.g. Tang et al. [7]. Our research is related to the work of Chakravarthy and Agnihothri [8]. They consider two customer types and allow employees to be cross trained or dedicated. A dedicated employee will only handle one type of customers while the cross trained employees can serve both types. For this setting they analytically derive insights with respect to the conditions for which either flexible, dedicated or a combination of the employee types is suitable. Our research looks at similar decisions but differs on some key points. First of all, the skill set that technicians can obtain in our study is more common in field services, i.e. there are low skilled (dedicated) technicians and highly skilled technicians. The highly skilled (cross trained) technicians can handle both emergencies and non emergencies while lower skilled technicians can only handle non emergencies. Consequently, there is an intrinsic need for some cross trained technicians to handle the emergencies. Moreover, we include traveling in our analysis. Finally, in our model demand is determined endogenously based on machine characteristics which makes it possible to study the relationship between maintenance and capacity decisions. All of the above mentioned papers assume a demand that is exogenously determined and as a consequence the demand experienced is independent of the capacity decisions. However, demand and capacity are intertwined for maintenance services: the maintenance policy pursued by the service provider clearly has an impact on the workload.

This brings us to the second related research field, i.e. the maintenance policy literature. In a maintenance policy the service provider stipulates how the machinery will be maintained. For an overview of the work in maintenance optimization we refer to Wang [9]. The maintenance policy has an immediate impact on the capacity decisions. Each preventive maintenance visit foreseen in the maintenance policy creates work for the technicians and the more preventive maintenance is being done the less repairs will be mandated. Although we will not explicitly consider the design of maintenance policies, we will model the failure behavior (reliability) of machines including the impact of maintenance on this failure behavior. By explicitly modeling the reliability of the machines covered by a maintenance contract we can evaluate different cross training strategies taking into account the interrelationship between service capacity and demand. We will apply a competing risk model, similar as discussed by Doyen and Gaudoin [10].

Hence, our work is situated on the crossroad between capacity and maintenance planning. Our main focus is on the evaluation of cross training decisions when demand changes in response to these capacity decisions. By using different scenarios we can determine whether the workload, the reliability of the machines or the maintenance policy has an impact on the optimal workforce configuration.

3 Field Service Model

In this section we will present the simulation model that is constructed in order to evaluate the possibility to deploy technicians dedicated to preventive maintenance. We captured the essence of a field service organization with a discrete time simulation model created in ARENA 11.0. To safeguard the applicability of our results we used real-life data from an existing service region of an OEM in the compressed air and generator industry. In the following paragraphs the assumptions and performance measures of the model will be discussed.

3.1 General Assumptions

In the service region under consideration 10 technicians or field service engineers (FSE) work to serve an installed base of machines. A significant part of this installed base is covered by comprehensive service contracts in which the OEM is responsible for both emergency and non emergency service. Demand from machines covered by a contract (D_{sc}) is more predictable than the demand of machines without a contract (D_r). Both D_{sc} and D_r can be a request for emergency or non emergency service. The key difference is that D_{sc} is influenced by the maintenance policy and the system state while D_r is independent of the OEM's maintenance policy and the system state. Therefore, we let jobs of D_r arrive according to a Poisson process and once executed the jobs are discarded. Machines with a service contract are explicitly modeled as entities in a closed-loop queuing system comparable to the approach in Papadopoulos [6]. Non emergency jobs on a machine under contract arrive with a fixed time interval dependent on the contract terms and the yearly operating hours of the machine**.** On the contrary, emergency jobs on a machine under contract arrive based on a failure process (see further). Between the different types of jobs we use a non-preemptive allocation priority for emergency jobs.

There are two types of technicians, i.e. technicians dedicated to non emergency service (N FSE) and fully cross trained technicians (E FSE) that can handle both emergencies and non emergencies.

One key advantage of non emergency jobs is the leeway in timely execution of these jobs. Preventive maintenance jobs are accepted to be on time if they are executed during an interval of 10% around the optimal preventive maintenance timing. This flexibility in timing of execution allows for non emergency jobs to be executed when there is idle capacity or to be postponed when work is piling up. Based on this reasoning and in order to capture the advantages of performing more preventive maintenance we allow that non emergency jobs can be started as soon as 10% before the timing foreseen in the maintenance contract (o_j). However, when the job is postponed for longer than 10% of the maintenance interval the job is considered to have become an emergency. We assume that when a failure occurs during the 10% interval around o_j both the repair and the preventive maintenance are performed during the same intervention.

3.2 Reliability of Machines

To model the maintenance demand originating from machines covered by a service contract (D_{sc}), we use a competing risk framework. In this framework a stochastic process representing failures and another representing preventive maintenance compete against each other to materialize.

In order to model the time until the next failure after maintenance job j (X_j) we have to quantify the impact of maintenance on the failure rate (λ). In the standard competing risk approach it is assumed that each maintenance is perfect, i.e. after receiving maintenance the machine is as good as new (AGAN). In reality this is not the case, therefore we assume that after emergency maintenance the failure rate of the machine is the same as just before the failure which is a more plausible assumption. For non emergency maintenance we keep the assumption of AGAN maintenance. As a consequence the failure intensity is determined by the time that has passed since the last preventive maintenance job on the machine (t_{pm}). We assume that the failure intensity function can be modeled by the widely used Power Law Process [11]:

$$\lambda(t_{pm}) = \frac{\beta}{\alpha}\left(\frac{t_{pm}}{\alpha}\right)^{\beta-1} . \qquad (1)$$

with α = scale parameter
β = shape parameter

For a Power Law intensity function the time to failure after a maintenance intervention j (X_j) can be represented as a truncated Weibull distribution.

$$X_j \sim Weibull\left(x \middle| x > t_{pm}\right) - t_{pm} \qquad (2)$$

The time to failure obtained in this way is in line with the Power Law process. We have linked the demand for service (emergency and non emergency) with the maintenance policy followed by the service provider. Moreover, the demand is dependent on the state of the service system. Indeed, when there is too much work to be done for the FSEs, preventive maintenance is stalled which will lead to more machines failures due to the increasing failure rate in function of t_{pm}.

4 Results

In this section we discuss the results of our simulations. We tested the attractiveness of deploying technicians dedicated to non emergency maintenance in a wide range of scenarios. The scenarios differ in terms of the maintenance policy (maintenance frequency), the total workload and the reliability of the machines. The maintenance policies considered are characterized by a preventive maintenance interval of either 2700 or 3000 machine operating hours. Four different levels of reliability for the machines are modeled by four sets of parameter values for the Power Law Process. Two possible workload level are considered, i.e. a low and a high workload. In total we use 16 different scenarios for which the optimal cross training policy is determined. By doing so, we obtain insights about the attractiveness of specialization in field services and about the factors that impact the cross training decision.

To evaluate the service performance we use two performance measures, i.e. average machine availability and a penalty function which contains the average response times for emergency and for non emergency service. Because the results based on these two performance measures differ only slightly, we restrict ourselves in this paper to the results based on the availability measure. For each scenario we will start with 10 E FSEs and gradually replace them with N FSEs. This evolution in the workforce mix can be captured by the ratio

$$R_n = \frac{S_n}{S_e + s_n}$$

with s_n the number of N FSE
s_e the number of E FSE .

When the number of technicians dedicated to non emergencies (S_n) increases the ratio goes up. We opted to maximize the service performance while keeping the budget for FSE constant. As a consequence, we start with a situation of 10 fully cross trained technicians (budget fully used) and progressively switch fully cross trained technicians for dedicated ones. Thanks to the fact that the cost of a N FSE amount only to 2/3 of the cost of an E FSE, two E FSEs can be replaced by three N FSE without exceeding the budget. So after switching one E FSE for one N FSE ($R_n =$ 0,1) we can replace two E FSE by three N FSE ($R_n = 0{,}27$), ... Among these workforce configurations we then select the one with which achieves the highest average availability for the machines under contract.

Having more N FSEs on the payroll can improve the timely execution of preventive maintenance jobs. This is a consequence of the fact that E FSEs give priority to emergencies before non emergencies. Therefore, preventive maintenance jobs are the first to be postponed, if there is a capacity shortage. This however endangers the timely execution of preventive maintenance. Without timely execution of preventive maintenance, the total number of emergencies rises due to machine breakdowns. This will in turn increase the need to postpone some jobs, once again endangering timely preventive maintenance and further increasing the number of emergencies ... The use of N FSEs can avoid this "emergency trap" of an escalating number of emergencies due to postponement of preventive maintenance. Replacing E FSEs by N FSEs has a direct and an indirect effect. Obviously, the lower number of technicians to handle emergencies will increase the response time for these emergencies while lowering the response time for non emergencies (direct effect). On the other hand the improvement in timely preventive maintenance will reduce the total number of emergencies which will reduce the response time for the remaining emergencies. This indirect effect of timely preventive maintenance on the number of emergencies may tip the balance in favor of employing more dedicated technicians.

Figure 1 shows the average availability for the scenario with preventive maintenance after each 3000 operating hours, a hazard function of PL(3175,10) and a high workload. The first FSEs which are reserved to perform only preventive maintenance strongly reduce the response time of both non emergencies and emergencies. As these FSEs will focus on non emergency service a lot of emergencies will be avoided (indirect effect), offsetting the increase in emergency response time due to the reduction of E FSEs (direct effect). So the introduction of the first N FSE increases the availability. But as the proportion of N FSE increases the positive effect on the number of emergencies decreases. The response time of non emergencies continues to decrease but this positive effect is canceled out by the increase in emergency response time. The increasing response time for emergencies deteriorates the availability of the machines. From figure 1 it is clear that a FSE configuration with a R_n of 0,27 is optimal with respect to the machine availability.

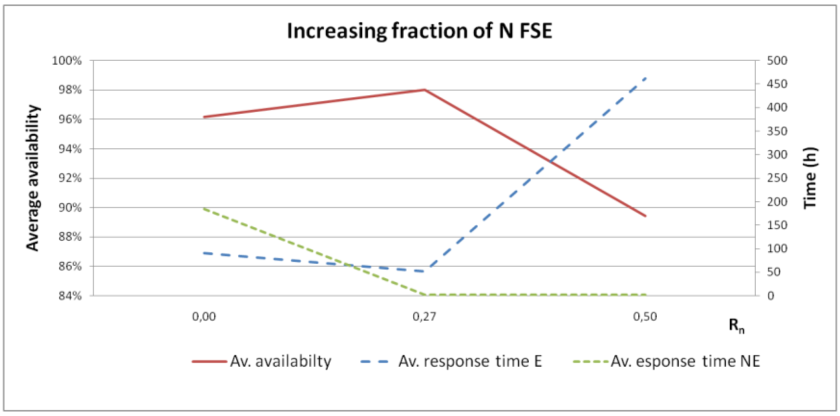

Fig. 1. Service performance with increasing specialization with high workload

It became clear from our simulation results that the evolution as shown in figure 1 only occurs when the workload is high. This observation can be explained by the fact that when the workload is not high, the E FSEs will have plenty of time to perform the non emergency services in a timely matter. It is only when E FSEs are overwhelmed by work that they will be pre-occupied by emergencies and neglect preventive maintenance. With the spotlight on emergencies, preventive maintenance will be postponed, further increasing the workload as more and more machines fail.

Table 1 gives an overview of the optimal R_n for the different scenarios based on a maximization of the availability. As can be seen from table 1, the optimal cross training policy is greatly depending on the workload and to a lesser extent on the reliability of the machines and the maintenance policy. The reliability and the maintenance policy play a role as they determine the steepness of the hazard function ,i.e. how fast the failure rate increases. With a steep hazard function at the moment on which preventive maintenance is due, employing N FSE becomes more attractive. We conclude that having N FSE becomes optimal if the workload is high and the failure rate increases fast (see figure 2).

Table 1: Optimal R_n with respect to availability

Maintenance policy	**Workload**	**PL(3175,5)**	**PL(3175,10)**	**PL(3175,15)**	**PL(4000,10)**
2700	Low	0	0	0	0
	High	0,27	0,27	0,27	0
3000	Low	0	0	0	0
	High	0,27	0,27	0,27	0

Full cross training is the preferred policy in many scenarios. This seems to contradict with previous research [8]. Several reasons can be postulated for the popularity of full cross training in our model. Firstly, as E FSE can handle any type of task the service organization minimizes the probability that customers have to wait because there is no suitable FSE. Secondly, we use a realistic cross training structure in which some types of jobs can only be handled by cross skilled workers. Finally, the conclusion that full cross training is often optimal seems to stroke with practices in reality.

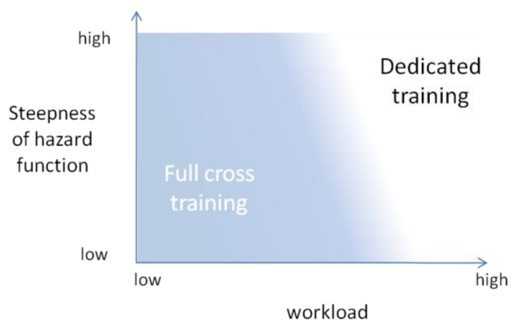

Fig.2 Graphical representation of factors influencing the cross training policy

5. Conclusion

In this paper we reported on the results of a simulation study in which we modeled the field service operations of an OEM in the compressed air and generator industry. The simulation model takes into account some of the key characteristics of field service systems such as traveling, job allocation in discrete time and the use of long term service contracts that combine preventive and corrective maintenance. As maintenance providers feel the pressure to deliver excellent service while containing costs, determining the optimal cross training policy becomes vital.
Employing technicians dedicated to preventive maintenance turns out to be optimal if the workload is high and/or the reliability of the machines is descending fast. The deployment of technicians dedicated to preventive maintenance (non emergencies) avoids that preventive maintenance is postponed too long due to more urgent machine failures. The timely execution of preventive maintenance on his turn will lower the total amount of machine failures possibly offsetting the negative effect of having less fully skilled technicians. However, full cross training is the dominant strategy for the scenarios that we tested. We evaluated the impact of the workload, the machine reliability, the contract penetration rate and the maintenance policy on the service performance using realistic data values. The workload is the principal factor of concern for cross training decisions but also the steepness of the hazard function plays a role.

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